Reading Material Personalization Searching in E-Learning

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Abstract

A student’s ability to grasp new concepts or knowledge from reading material is crucial and dependent on their personalization. Personalization can be identified using learning style. In e-learning, identifying learning style, and matching reading material based on learning style, is critical for students; as it may affect their learning progress and their rate of absorbing information. Therefore, it is crucial for students to be able to locate reading material that best matches their particular learning style. The objective of this paper is to develop a tool that can help retrieve reading material based on personalization. By using a collaborative filtering method, this tool will be able to help students locate reading material that best matches their learning style in e-learning. The architecture and components of the tool are discussed.

1. Introduction

E-learning is an approach to learn and develop using a collection of learning methods in digital technologies, which enable, distribute and enhance learning (Trika, Ana, & Singaraja, 2002). Based on that definition, an e-learning website can be defined as a web-based system that is designed to support learning and teaching processes to the user. Reading material is one of the most commonly used learning materials in e-learning. Reading is a fundamental skill that each person needs to develop during early childhood and continue to enhance into adulthood (Cechinel et. al, 2013). Students need reading material to carry out activities, such as solving problems, making decisions, reducing uncertainties, resolving conflicts, answering questions and satisfying curiosities. It helps them understand their courses. Students should read suitable reading material in order to become effective readers.

However, most students have difficulty finding suitable reading material due to information overload and differentiation in reading material presentations. Reading materials differ due to the differentiation of levels and forms of how authors present their information. A student's ability to grasp new concepts or knowledge from reading material is crucial and dependent on their personalization or learning style (Honey & Mumford, 1992; Fleming, 1995). Students experience difficulty if reading materials do not match their particular learning style; because each individual has a different type of learning style. The mismatch of reading material with student learning style causes student to lose interest in their learning progress. Students usually depend on teachers or tutors to select their reading material. There is currently no e-learning software that can help with recommending suitable reading material based on personalization. This paper aims to develop a tool that can help retrieve reading material based on personalization. The tool will be upgraded from the existing Learning Style based Information Seeking tool (Shuib & Abdullah, 2013), by using collaborative filtering method technology, in order to assist students in finding their reading material. Personalization can be identified using learning style. Several studies have revealed that learning can be enhanced through the presentation of materials that are consistent with a student's particular learning style (Budhu, 2002; Pen˜a et al., 2002; Stash et al., 2004).

2. Literature Review

Reading materials are written documents to be read. They contain data that is organized in the form of meaningful information (Shuib & Abdullah, 2013). Information in reading material can be presented in various forms, such as text, tables, pictures, flowcharts, drawings, maps, figures and mathematical expressions (Shuib, 2013). The presentation of these forms denotes how the author explains or demonstrates their information in reading material to readers. The appropriate presentation of information in reading material plays an important role; because it enhances the reader's ability to understand and effectively gain more knowledge for them to apply in a learning activity. Most reading material can be found online (Ghauth & Abdullah, 2010). Many organizations and publishers today have digitized the printed their reading material, to give easy access to users anywhere and anytime.

With increasing access to the internet, the amount of information is growing exponentially; thus leading to information overload problems. For this reason, students are faced with difficulties of obtaining suitable reading material. This is largely because students are unaware of their own learning style. To compound this problem, reading materials are not classified according to the way authors present their information.

Personalization can be applied via learning style. In this study, we use the VARK learning style by Fleming and Mill (1992), because it uses sensory modality. Sensory modality involves the merging of perception and memory, with due consideration to the way the mind receives and accumulates information. With the utilization of sensory modality, the elements that constitute the four learning style preferences, which are Visual (for learners who prefer information presented in a visual form), Aural (for learners who prefer information that is listened to or verbalized), Read/write (for learners who prefer information presented in a text form) and Kinesthetic (for learners who prefer learning by example, action, practice and experience), can be differentiated and appropriately mapped to the reading material.

2.1 E-learning

E-learning is usually designed for educational purposes. Information is delivered online for the purpose of education, training, or knowledge management (Sun and Xie, 2009). Many researches have implemented learning style in their e-learning; known as personalized e-learning. In personalized e-learning, learning materials are presented in a way that best fits the learning style of each student. Table 1 shows examples of personalized e-learning. Several terms within the table need to be defined for a clearer understanding;

- Formative assessment - short tests and quizzes, questions and answering the lesson, assignments, homework, and so on
- Learning content - topic of the course
- Learning object - entities that can be used to support learning
- Learning path – a defined path to follow learning content
- Learning strategies – type of learning object that the student should learn

Table 1: Personalized e-learning

Author	**Learning Resources**	**System Output**	**Learning Style**
Klašnja-Milićević *et. al* (2011)	Formative Assessment	Learning Path	Yes
Yaghmaie and Bahreininejad (2011)	Learning Content	Learning Strategies	Yes
Yang *et. al* (2009)	Learning Content and Formative Assessment	Learning Path	Yes
Baribi *et al* (2009)	Learning Object	Learning Strategies	Yes
Cheng (2009)	Learning Object	Learning Strategies	Yes
Hassan (2009)	Learning Object	Learning strategies	Yes
Rogers (2009)	NA	Learning strategies	Yes
Savic and Konjovic (2009)	Learning Content	Learning strategies	Yes
Apriyani and Hasibuan (2008)	Learning Object	Learning strategies	Yes
Rafe and Manley (2008)	NA	Learning strategies	Yes
Graf et al. (2007)	Learning Object	NA	Yes

Based on a comparison study, most e-learning used learning style only to accommodate students with learning material that was specially designed for the system (Klašnja-Milićević et al. 2011; Yaghmaie and Bahreininejad 2011). This leads to problems, such as the need to provide content in multiple formats to suit student learning style. If the material is unavailable, specially designed material needs to be created. This requires a lot of time and money.

2.2 Recommender system

Recommender system has been a very active research topic for two decades (Cleger-Tamayo, Fernández-Luna & Huete, 2012; Bobadilla et al., 2013). It is used widely in various domains, such as business and education (Liao et al., 2010; Shuib et al., 2015). With the increase of learning objects in e-learning, recommender systems have become an important component of personalized e-learning services and are essential for e-learning providers to remain competitive (Wan, Jamaliding & Okamoto, 2011). The most popular method in recommender system is collaborative filtering. The collaborative filtering method is user-to-user correlation that uses group opinions to recommend items to individuals. This method computes similarities between user preferences and recommends items based on ratings provided by users whose preferences are similar to those of the given user and recommends items that they liked. The collaborative filtering method can be broken down into three categories according to their algorithmic techniques, which are memory based, model based and hybrid based (Bobadilla, Serradilla & Bernal, 2010; Shuib et al., 2015). The collaborative filtering technique is used widely in the business domain (Shendage, 2014).

The knowledge based method recommends items based on their functional knowledge. This functional knowledge contains knowledge about how a particular item meets a particular user's needs (Burke, 2000). This approach solves early rater and scarcity problems, because it does not depend on user ratings. The early rater problem is when new items, that have not had many ratings, cannot be easily recommended (Burke, 2002). Therefore, this approach complements the others (Burke, 2000). However, there is no recommender system in e-learning that implements this method.

3. Method

The method of this research study consists of four phases (as shown in Figure 1):

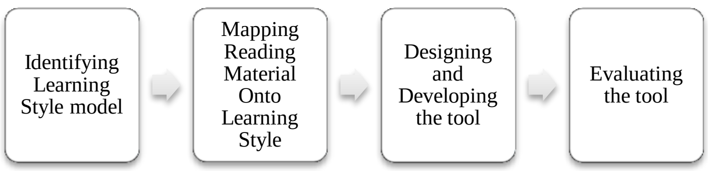

Figure 1: Research Methods

Identifying learning style model

The VARK learning style, by Fleming and Mill (1992), was used because it uses sensory modality and the suitability of preferences with reading material primitive elements. VARK consists of Visual, Audio Read/Write and Kinesthetic preferences (Fleming, 2010).

Mapping reading material onto learning style

Primitive elements in reading material are mapped onto learning style preferences (as shown in Table 2). For the audio preference, other preference components are used.

Table 2: Mapping reading material onto learning style preference

LS Preference	**Identifier**
Visual	Figure, diagram, map, chart, graph, flowchart, arrow, circle, hierarchy, hierarchies, picture, table, equation, notation, formula, histogram, scatter plot, screenshot
Read/write	All words except words describing Visual and Kinesthetic preference
Kinesthetic	Example, practice, case study, exercise, simulation, experiment, self-assessment, application

Designing and developing the tool

The system was designed and developed using a web base system. Figure 2 shows the architecture of the system. The architecture has five components, which are Input, Output, Database, LS based Search and Feedback. Each component is discussed in the next section.

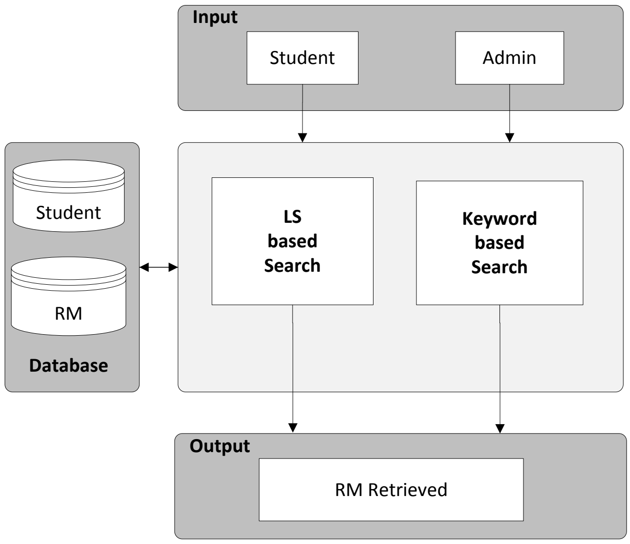

Figure 2: Proposed architecture in Book Spot

Evaluating the tool

The system will be evaluated using a technology acceptance model. The Technology Acceptance Model (TAM) proposes the perceived ease of use and perceived usefulness to predict applications usage (Masrom, 2007).

4. Book Spot!

The tool's name is Book Spot! In this section, each of the modules shown in Figure 2 will be discussed:

Figure 3: Book Spot! Home Page

Input module

This module receives information from user's profile, such as learning style test and search query. This input is used to develop a user model for learning style based search and is stored in the user's database. Furthermore, the input module also receives the reading material data, such as title, author, pdf file, topic and learning style category from the administrator.

LS based search module

This module maps and matches students with reading material based on the students' preferences. Students need to fill in a search query. The system matches between learning style components in reading material and the students' preferences using knowledge based method.

Output module

Reading materials that match the students' search query and have a high similarity with the students' preferences will appear in the results. Each reading material can be evaluated by the student.

Database module

The database module has two types of database, namely the student database and the reading material database. The student database consists of student profile, learning style record and evaluation. The reading material database contains the documents and ratings from the user.

Feedback Module

Feedback is based on user-user rating. This module recommends the best reading materials to the new user based on ratings from previous users that had similar preferences.

Figure 4: Input rating from retrieve document

5. Evaluating the Tool

In this study, a TAM was used to evaluate the usability of the study. Perceived ease of use, perceived usefulness and user satisfaction for Book Spot were evaluated. Evaluation forms were distributed to users. The TAM was applied to evaluate the Book Spot system to measure system performance.

- Ease of use - The functionalities of user interface interaction are, ease to use, friendly user interface, effectively saving the users' time finding suitable reading materials, and selecting reading material quickly, based on users' preferences.
- Usefulness - Effective use of the Book Spot system in progress learning, improve the users' understanding in reading and increase awareness of the student's learning style.
- User satisfaction - Quickly accomplishes student tasks and gain student confidence in learning progress.

Figures 5 to 7 show the results from the user's evaluation of the Book Spot system.

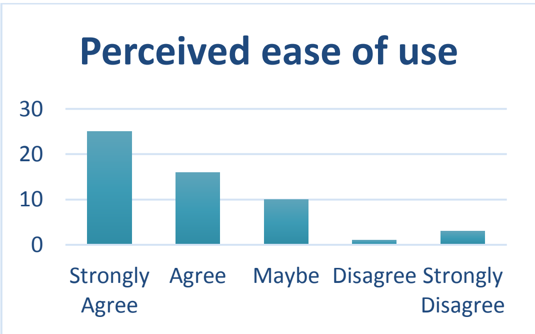

Figure 5: Perceived ease of use book spot

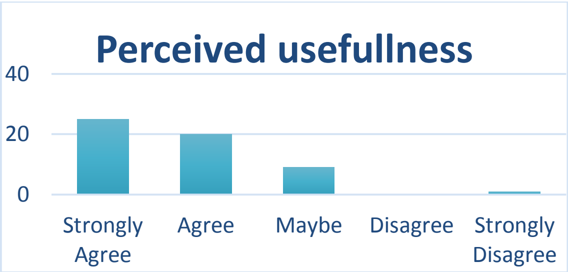

Figure 6: Perceived usefulness book spot

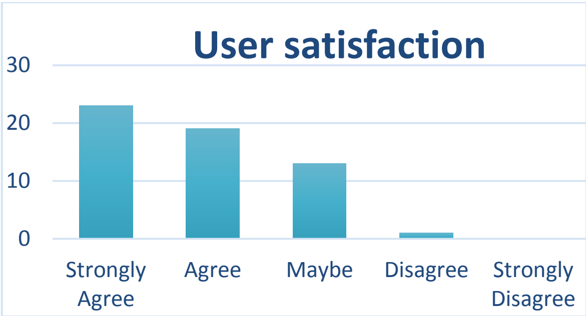

Figure 7: User satisfaction on book spot

The results show that users agreed that Book Spot is easy to use, useful and has satisfactory tools.

6. Conclusion

In e-learning, identifying learning style and matching reading material based on learning style is critical for students, as it may affect their learning progress and their rate of absorbing information. It is therefore crucial for students to be able to locate reading material that best matches their learning style. Using the knowledge based and collaborative filtering method can help students to locate reading materials that best match their learning style in e-learning. This will improve their e-learning efficiency.

7. Acknowledgement

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